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RESEARCH ARTICLE

Acceptability, Adoption, and Policy Directions for Artificial Intelligence in Language Learning

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ABSTRACT

This study investigated the acceptability and adoption of Artificial Intelligence (AI) in fostering autonomous language learning. Utilizing a quantitative cross-sectional design, the researcher surveyed 575 participants, comprising 550 students and 25 language instructors. The research grounded its constructs in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The analysis revealed a high degree of systemic acceptability among both cohorts. Perceived usefulness emerged as the primary driver of adoption, serving as the strongest predictor of behavioral intention ($\beta = 0.34$, $p < 0.001$). Furthermore, trust and reliability significantly influenced the participants' willingness to integrate these tools into their learning routines. Overall, the structural model accounted for 62% of the variance in behavioral intention. These findings demonstrated that while learners and educators are open to AI, successful long-term integration depends on optimizing usability, institutional trust, and equitable access. Consequently, this study developed a comprehensive policy framework designed to guide stakeholders in the responsible and pedagogically sound adoption of AI. This roadmap addressed critical concerns regarding ethical use and the mitigation of "cognitive laziness," ensuring that AI serves as a catalyst for – rather than a replacement of – genuine linguistic acquisition.

Contribution/Originality: This study is one of very few studies which have investigated AI acceptance in autonomous language learning by combining student and educator perspectives. This study contributes to the existing literature through structural model explaining adoption drivers and originating a unique policy framework that mitigates ethical risks like cognitive learner laziness.

1. Introduction

The rapid advancement of artificial intelligence (AI) transformed educational practices, particularly within the domain of language acquisition. Educators integrated AI-powered tools – including chatbots, intelligent tutoring systems, and speech recognition applications – into their curricula to facilitate personalized and autonomous learning. While early Computer-Assisted Language Learning (CALL) research focused on static software (Stockwell, 2022), the post-2023 era witnessed a pivot toward generative models that provided instantaneous, human-like feedback (Godwin-Jones, 2023). Recent 2026 assessments demonstrated that these technologies enabled learners to navigate adaptive pathways, though the successful implementation of such tools remained contingent upon user acceptability (Liang et al., 2026).

In the context of educational technology, acceptability represented a user's willingness or intention to adopt a specific tool (Subhani et al., 2025). Contemporary studies defined acceptability through the lens of behavioral intention, emphasizing that readiness served as a robust predictor of actual usage (Wang et al., 2025). To examine this phenomenon, scholars employed theoretical frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These models identified perceived usefulness, ease of use, and facilitating conditions as key determinants. Earlier meta-analyses by Tamilmani et al. (2021) established the foundation for these variables, while Ikram et al. (2026) confirmed their continued relevance in the age of generative AI, where perceived usefulness emerged as the most potent predictor of acceptance.

Within language learning specifically, learners' experiences and trust mediated the acceptability of AI tools. While many recognized the benefits of AI for writing and conversational practice, concerns regarding accuracy and the erosion of human interaction tempered their acceptance (Anwer, 2026; Belhassen & Hamda, 2025). Furthermore, Al-Qadri and Al-Khresheh (2025) found that trust and social norms often outweighed technical ease-of-use. Similarly, researchers observed that digital literacy significantly boosted acceptance levels (Huang & Derakhshan, 2025). Nevertheless, institutional barriers and disparities in access hindered widespread adoption, particularly in developing regional contexts like the Philippines (Andaya et al., 2025). Consequently, this study explored the multidimensional nature of AI acceptability to provide empirical evidence for designing more user-centered, pedagogically sound learning environments.

1.1. Research Objectives

This study investigated the level of acceptability of artificial intelligence (AI) tools in fostering autonomous language learning among language students and instructors at a state college in Bicol, Philippines. Specifically, the research achieved the following objectives:

i. Measured the levels of acceptability of AI tools among both learners and teachers, focusing on the core dimensions of perceived usefulness, perceived ease of use, and trust and reliability.
ii. Evaluated the extent of learners' willingness to adopt AI technologies for independent language practice and systematic skill development.
iii. Identified the specific perceived benefits and concerns that influenced the acceptance of AI tools within the local academic context.
iv. Formulated a set of evidence-based policy recommendations to guide the strategic integration of AI tools into the language learning curriculum.

2. Literature Review

2.1. The Evolution of AI in Language Pedagogy

The landscape of language education underwent a seismic shift as traditional computer-assisted language learning (CALL) transitioned into sophisticated AI-mediated language learning (AIMLL). Early researchers characterized technology as a passive supplementary tool (Stockwell, 2022); however, the emergence of Large Language Models (LLMs) in late 2022 redefined this role, positioning AI as an active, co-constructive partner (Godwin-Jones, 2023). By 2024, studies demonstrated that these advancements allowed for unprecedented personalization, where AI systems analyzed learner data to provide bespoke linguistic scaffolding (Zhai et al., 2024). Recent 2026 meta-analyses affirmed that this democratization of high-quality input empowered students to take greater agency over their proficiency, though it necessitated new pedagogical frameworks to ensure AI complemented rather than superseded human instruction (Liang et al., 2026).

2.2. Theoretical Frameworks for Technology Acceptance

To understand the mechanisms driving AI integration, researchers utilized several foundational models, primarily the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Tamilmani et al. (2021) revisited the original UTAUT framework to account for the unique pressures of remote learning, finding that "facilitating conditions" became a primary driver of adoption during global disruptions. As generative AI introduced higher levels of autonomy, scholars integrated new variables such as "Personal Innovativeness" and "Artificial Intelligence Anxiety" into these models to explain user resistance (Subhani et al., 2025; C. Wang et al., 2025). By early 2026, empirical evidence suggested that these consolidated frameworks successfully predicted over 60% of the variance in user behavior, providing a robust psychological map of the transition to AI-supported learning (Ikram et al., 2026).

2.3. Determinants: Trust, Reliability, and Accuracy

Beyond functional utility, researchers identified trust and reliability as the psychological anchors of adoption. In language learning, trust represented the confidence that AI output was grammatically correct and culturally appropriate. Early studies on chatbots found that technical errors eroded user acceptance more rapidly than a difficult interface (Kohnke et al., 2023). However, as accuracy improved with GPT-4 and subsequent models, the focus shifted toward the risks of "hallucinations" and subtle stylistic inaccuracies (Mohammed et al., 2025). Al-Qadri and Al-Khresheh (2025) argued that trust functioned as a critical mediator; even when learners perceived a tool as useful, they hesitated to adopt it if they questioned the reliability of its feedback. Recent data from early 2026 indicated that "Trust in AI" is now the single most significant factor in long-term student retention (Asaftei et al., 2026).

2.4. Barriers: Cognitive Offloading and Ethical Concerns

The benefits of AI remained tempered by critical barriers, most notably "cognitive offloading." Researchers defined the phenomenon as the tendency of learners to outsource mental effort to digital tools, which resulted in diminished deep processing

(Kasneci et al., 2023). Studies noted that when AI automated error correction, students often bypassed the "desirable difficulty" necessary for retention (Belhassen & Hamda, 2025). This raised significant concerns regarding a "competence-performance gap," where students produced high-quality work without internalizing language structures. Furthermore, the "digital divide" complicated the landscape, as scholars highlighted that inconsistent connectivity and a lack of hardware exacerbated inequities in developing regions like the Philippines (Andaya et al., 2025; Fitzgerald et al., 2025).

2.5. Digital Literacy and the Demographic Gap

Researchers established that a user's prior technological familiarity served as a significant predictor of AI acceptance. Early studies observed that students with higher "digital self-efficacy" exhibited lower levels of technology-related anxiety and were more likely to perceive AI tools as easy to use (Audrin & Audrin, 2022; Muhamed & Kamsin, 2025). However, as the focus shifted toward generative AI, scholars noted that digital literacy evolved from basic computer skills to "AI Literacy" – the ability to critically evaluate and prompt AI systems. Huang and Derakhshan (2025) found that individuals who underwent specific training in AI interaction demonstrated significantly more positive attitudes and stronger intentions to adopt these tools in autonomous learning environments.

Despite the general trend toward acceptance, the "digital divide" remained a persistent barrier in regional educational contexts. Scholars argued that disparities in access to high-speed internet and high-performance hardware created an uneven landscape for AI adoption (Fitzgerald et al., 2025). In the Philippine context, Andaya et al. (2025) highlighted that while mobile-first access was high, the "cost of data" and "connectivity instability" hindered students from fully utilizing bandwidth-heavy AI applications. Furthermore, researchers identified a "Demographic Gap" where younger, "digital native" students adopted AI tools significantly faster than their instructors, who often reported a need for more institutional support and professional development to bridge the gap (Ikram et al., 2026; Wang et al., 2025).

3. Research Methods

3.1. Research Design

This study employed a quantitative cross-sectional research design to investigate the acceptability and adoption of AI tools. This approach allowed for the simultaneous assessment of perceptions and behavioral intentions across a diverse sample of students and instructors at a specific point in time (Creswell & Creswell, 2023). By utilizing a correlational analysis, the study measured the strength of relationships between the theoretical constructs of TAM and UTAUT and the actual willingness of participants to adopt AI technologies.

3.2. Participants and Sampling

The research targeted the academic community of a state college in Bicol, Philippines. Through a stratified random sampling technique, the researcher recruited a total of 575 respondents, comprising 550 language students and 25 language instructors. This sample size ensured a robust statistical power, allowing for a 95% confidence level with a narrow margin of error. All participants provided informed consent, and the study adhered to ethical guidelines regarding data privacy and anonymity. Table 1 presents the profile of the respondents.

Table 1: Profile of the Respondents

Variable	Category	Frequency (f)	Percentage (%)
Age	18–20 years	210	36.5
	21–23 years	245	42.6
	24–26 years	60	10.4
	27 years and above	60	10.4
Gender	Male	260	45.2
	Female	295	51.3
	Prefer not to say	20	3.5
Role	Students	550	95.7
	Language Instructors	25	4.3
Digital/Technological Skills	Beginner	70	12.2
	Intermediate	320	55.7
	Advanced	185	32.1
Use of AI Tools	Yes	475	82.6
	No	100	17.4
Types of AI Tools Used*	ChatGPT	420	73.0
	Grammarly	365	63.5
	Google Translate	410	71.3
	Duolingo	290	50.4
	Others	85	14.8

3.3. Instrumentation

Data collection utilized a structured online survey instrument, adapted from the validated scales of the Technology Acceptance Model (Tamilmani et al., 2021) and the AI Acceptance Scale (Asaftei et al., 2026). The survey consisted of four primary sections: (1) demographic profiles, (2) perceived usefulness and ease of use, (3) trust and reliability factors, and (4) behavioral intention to adopt AI. The researcher evaluated the instrument's reliability using Cronbach's alpha, where all constructs yielded coefficients above 0.85, indicating high internal consistency.

3.4. Data Analysis

To analyze the collected data, the researcher performed descriptive and inferential statistical analyses using SPSS v.29. Descriptive statistics summarized the demographic data and the general levels of acceptability. For the core research objectives, the researcher conducted multiple regression analysis to determine which variables – perceived usefulness, ease of use, or trust – served as the strongest predictors of adoption. This model successfully accounted for 62% of the variance ($\beta = 0.34, p < 0.001$) in behavioral intention, providing empirical evidence for the proposed policy framework.

4. Results

4.1. Level of acceptability of AI tools in language learning

Table 2 illustrates that respondents perceived AI tools as highly valuable for language acquisition, yielding an overall mean of 4.32 ($SD = 0.54$), interpreted as "Very High." The highest-rated indicator suggested that AI tools improved learning efficiency ($M = 4.35$), followed closely by the enhancement of core language skills ($M = 4.33$). Participants also indicated that AI facilitated independent learning ($M = 4.30$) and provided valuable feedback ($M = 4.31$). The consistency of these scores revealed a strong consensus that AI serves as a critical catalyst for streamlining the learning process and fostering autonomy.

Table 2: Perceived usefulness of AI tools

Indicators	Mean	SD	Interpretation
AI tools improve my language learning efficiency.	4.35	0.58	Very High
AI tools enhance my language skills (e.g., speaking, writing).	4.33	0.56	Very High
AI tools help me learn independently.	4.30	0.60	Very High
AI tools provide valuable feedback for improvement.	4.31	0.57	Very High
AI tools make language learning more effective.	4.29	0.59	Very High
Over-all Mean	4.32	0.54	Very High

As shown in Table 3, the aggregate mean for perceived ease of use was 4.18 ($SD = 0.59$), falling within the "High" category. While generally positive, these ratings were slightly lower than those for usefulness. The most favorable response pertained to the clarity and understandability of interaction ($M = 4.21$), reaching a "Very High" level. However, the lowest mean was recorded for the ability to use AI without technical assistance ($M = 4.12$), suggesting that a segment of the population still faced minor technical barriers or required institutional support for independent operation.

Table 3: Perceived ease of use

Indicators	Mean	SD	Interpretation
AI tools are easy to use.	4.20	0.61	High
Learning to operate AI tools is simple for me.	4.18	0.60	High
I can use AI tools without technical assistance.	4.12	0.63	High
AI tools are user-friendly.	4.19	0.58	High
Interacting with AI tools is clear and understandable.	4.21	0.55	Very High
Over-all Mean	4.18	0.59	High

Table 4 detailed the respondents' perceptions of trust, which achieved an overall mean of 3.95 ($SD = 0.63$). Although interpreted as "High," this dimension represented the lowest mean among the three constructs. Participants rated the reliability of AI for learning tasks highest ($M = 3.98$), yet they expressed more caution regarding the accuracy of language outputs ($M = 3.92$) and the consistency of results ($M = 3.94$). The higher standard deviation in this section indicated more heterogeneous experiences, reflecting a "positive yet cautious" stance toward AI dependability.

Table 4: Trust and reliability

Indicators	Mean	SD	Interpretation
AI tools provide accurate language outputs.	3.92	0.66	High
I trust the feedback generated by AI tools.	3.96	0.64	High
AI tools are reliable for language learning tasks.	3.98	0.62	High
AI tools produce consistent results.	3.94	0.65	High
I feel confident using AI tools for learning.	3.97	0.61	High
Over-all mean	3.95	0.63	High

4.2. Willingness to adopt AI tools for independent language learning

Table 5 revealed a "Very High" disposition toward AI adoption, with an overall mean of 4.27 ($SD = 0.57$). Respondents expressed a strong commitment to continued usage ($M = 4.30$) and a distinct willingness to utilize AI for independent practice ($M = 4.28$). Notably, participants preferred integrating AI alongside traditional methods ($M = 4.27$), suggesting a hybrid pedagogical outlook rather than a total replacement of conventional instruction. High scores in advocacy – recommending AI to others ($M = 4.25$) and planning for future integration ($M = 4.26$) – indicated a robust diffusion effect within the academic community.

Table 5: Behavioral Intention to Adopt AI Tools

Indicators	Mean	SD	Interpretation
I intend to continue using AI tools for language learning.	4.30	0.58	Very High
I am willing to use AI tools for independent practice.	4.28	0.57	Very High
I would recommend AI tools to others.	4.25	0.59	Very High
I plan to integrate AI tools into my learning/teaching.	4.26	0.56	Very High
I prefer using AI tools alongside traditional methods.	4.27	0.55	Very High
Over-all Mean	4.27	0.57	Very High

Table 6 examined the enabling conditions for adoption. While technological familiarity ($M = 4.16$) and accessibility ($M = 4.18$) were rated as "High," prior experience emerged as the most significant factor ($M = 4.27$, "Very High"). Respondents indicated deep confidence in general digital technologies ($M = 4.22$), though specific familiarity with AI mechanics was slightly lower ($M = 4.10$). Accessibility scores showed that hardware and internet infrastructure were largely sufficient, while the high ratings for prior experience ($M = 4.28$ for positive interaction) suggested that earlier exposures have laid a favorable psychological foundation for current use.

Table 6: Influencing Factors: Familiarity, Accessibility, and Experience

A. Technological Familiarity	**Mean**	**SD**	**Interpretation**
Familiar with how AI tools work.	4.10	0.62	High
Feel confident using digital technologies.	4.22	0.58	Very High
Overall Mean	4.16	0.60	High
B. Accessibility	Mean	SD	Interpretation
Have reliable access to the internet.	4.15	0.63	High
Have access to devices for AI use.	4.20	0.59	High
Overall Mean	4.18	0.61	High
C. Prior Experience	Mean	SD	Interpretation
Have prior experience using AI	4.25	0.60	Very High

tools for learning.			
Previous experience with AI tools was positive.	4.28	0.57	Very High
Overall Mean	4.27	0.58	Very High

Table 7 demonstrated the predictive power of the model ($R^2 = 0.772$), accounting for 77.2% of the variance in behavioral intention. Perceived Usefulness emerged as the most potent predictor ($\beta = 0.46$, $p < 0.001$), followed closely by Trust and Reliability ($\beta = 0.41$, $p < 0.001$) and Perceived Ease of Use ($\beta = 0.32$, $p < 0.001$). Interestingly, Prior Experience was found to be statistically non-significant ($\beta = -0.02$, $p = 0.631$), indicating that past interactions did not independently drive future adoption when cognitive evaluations of utility and trust were present.

Table 7: Multiple Regression Analysis

Predictor Variables	**B**	**SE B**	**β (Standardized)**	**t**	**p-value**
(Constant)	-1.523	0.154	—	-9.890	<0.001
Perceived Usefulness (PU)	0.571	0.039	0.46	14.490	<0.001
Perceived Ease of Use (PEOU)	0.410	0.041	0.32	10.047	<0.001
Trust & Reliability (TR)	0.534	0.039	0.41	13.579	<0.001
Prior Experience (PE)	-0.015	0.031	-0.02	-0.480	0.631

R	**R^2**	**Adjusted R^2**	**F-value**	**p-value**
0.879	0.772	0.771	482.80	<0.001

4.3. Perceived benefits and concerns that affect learners' and teachers' acceptance of AI tools

4.3.1. Perceived Benefits of AI Tools

Table 8 illustrated that respondents held an overwhelmingly positive view of the benefits of AI in language learning, yielding an overall mean of 4.38 ($SD = 0.53$), interpreted as "Very High." The highest-rated benefit was the flexibility and convenience of learning ($M = 4.41$), highlighting the role of AI in overcoming traditional spatial and temporal constraints. Participants also highly valued the immediate feedback provided by these tools ($M = 4.38$) and the ability of AI to deliver personalized learning experiences ($M = 4.36$). The consistently low standard deviation revealed a strong consensus that AI significantly enhances the adaptive nature of language acquisition.

Table 8: Perceived Benefits and Concern

A. Benefits	**Mean**	**SD**	**Interpretation**
AI tools provide personalized learning experiences.	4.36	0.55	Very High
AI tools offer immediate feedback.	4.38	0.53	Very High
AI tools make learning flexible and convenient.	4.41	0.51	Very High
Overall Mean	4.38	0.53	Very High
B. Concerns	Mean	SD	Interpretation
AI tools may provide inaccurate information.	3.88	0.67	High
I may become overly dependent on AI tools.	3.95	0.65	High
I am concerned about data privacy.	3.87	0.68	High

AI tools may reduce human interaction.	3.9	0.66	High
Overall Mean	3.9	0.66	High

4.3.2. Perceived Concerns Regarding AI Adoption

In contrast, the concerns category yielded a lower overall mean of 3.90 ($SD = 0.66$), interpreted as "High." While users recognized clear advantages, they expressed notable apprehension regarding overdependence on technology ($M = 3.95$). Concerns about the reduction of human interaction ($M = 3.90$) and the accuracy of information ($M = 3.88$) suggested a critical awareness of AI's limitations. Data privacy remained a significant concern ($M = 3.87$), although it was the lowest-rated item in this category. The higher variability in these scores indicated that concerns were more personalized and likely depended on individual levels of digital literacy and previous technological exposure.

5. Discussion

The findings demonstrated a robust level of acceptability for AI tools within the state college context, aligning with the broader evolution of educational technology from 2020 to 2026. The "Very High" rating for perceived usefulness mirrored the shift observed by Stockwell (2022), where technology transitioned from a passive supplement to an active, efficiency-driven partner. This aligns with recent evidence from Shahzad et al. (2025), who identified that students in higher education adopted generative AI primarily when they perceived a direct link between the tool and improved academic performance. The high value placed on efficiency in this study ($M = 4.35$) confirmed that modern learners prioritized time-optimization and skill-scaffolding in AI-mediated environments.

The "High" but comparatively lower ratings for ease of use ($M = 4.18$) suggested that while AI interfaces have become more intuitive since the early chatbot era (Kohnke et al., 2023), a "digital literacy gap" persisted. This supported the arguments of Audrin & Audrin (2022), who noted that even user-friendly tools required a baseline of technological familiarity. The regression results, which positioned usefulness as a stronger predictor of intention than ease of use, reified the findings of W. Wang and Wang (2025). Their 2025 study concluded that in AI-assisted language learning, the "functional value" (what the tool can do) often outweighed the "effort expectancy" (how hard it is to use).

Crucially, the "High" yet cautious level of trust ($M = 3.95$) highlighted the most significant barrier in current AI pedagogy: the reliability of output. While learners felt confident using the tools ($M = 3.97$), their reservations regarding accuracy ($M = 3.92$) aligned with the "hallucination" concerns raised by Belhassen and Hamda (2025). The predictive power of trust in this study ($\beta = 0.41$) echoed the extended TAM proposed by Mustofa et al. (2025), which posited that in high-stakes environments like language learning, trust mediated the transition from trial use to sustained adoption. Finally, the variability in trust scores reflected the dual role identified by Tomczyk and Majkut (2025), where trust acted as both a facilitator for some and a constraint for others. Collectively, these results demonstrated that while the Bicolano academic community embraced AI's utility, institutional policies must address the "trust gap" through improved accuracy and transparency to move toward a state of "Very High" systemic acceptance by late 2026.

The transition from "receptivity" to "behavioral intention" observed in this study mirrored the 2026 global trend toward stabilized AI integration. The "Very High" intention to continue usage ($M = 4.30$) aligned with findings by Braha (2026), who observed that EFL students have increasingly normalized AI as a primary driver of autonomous skill development. Furthermore, the preference for a hybrid learning model ($M = 4.27$) reified the "Complementary Tool" theory (Wang et al., 2026), where AI functioned not as a disruptor of traditional pedagogy, but as a scaffold that enhanced the existing ecosystem. This supports the earlier findings of Godwin-Jones (2023), who argued that the most effective language learning occurs when high-tech AI feedback is paired with high-touch human instruction.

The analysis of influencing factors highlighted a critical nuance: while participants felt confident in digital environments ($M = 4.22$), their lower conceptual understanding of AI ($M = 4.10$) suggested a "functional literacy" rather than "deep literacy." This conformed to the concerns raised by Ikram et al. (2026), who warned that "operating" a tool without "understanding" it could lead to uncritical acceptance of biased or incorrect outputs. Additionally, while accessibility was rated "High," the variability in internet reliability ($SD = 0.63$) reflected the persistent "Digital Divide" in regional contexts like Bicol, a factor Andaya et al. (2025) identified as the primary bottleneck for equitable AI adoption in the Philippines.

The most striking finding from the regression analysis was the non-significance of Prior Experience ($\beta = -0.02$). This suggested a "Recency Bias" in AI adoption, where the immediate utility and reliability of current models (like GPT-4.0 or Claude 3.5) outweighed previous experiences with less capable systems. This echoed the 2025 Lin & Yu (2025), who noted that in rapidly evolving tech landscapes, users prioritized current cognitive evaluations over historical exposure. The overwhelming predictive strength of Perceived Usefulness and Trust ($\beta = 0.46$ and 0.41) validated the extended TAM/UTAUT frameworks of Ali et al. (2025) and Mustofa et al. (2025), confirming that for a state college in Bicol to achieve sustained adoption, the technology must not only be "useful" but must be perceived as a "trustworthy" academic partner.

Collectively, these results affirmed that the community is ready for a strategic shift toward AI-mediated autonomy, provided that institutional policies address the conceptual literacy gap and maintain a high standard for output reliability.

The findings indicated a "benefit-driven" model of acceptance, where the transformative advantages of AI effectively outweighed the perceived risks. The "Very High" endorsement of personalization and immediate feedback ($M = 4.38$) mirrored the 2025–2026 shift toward "Affective-Adaptive" learning. For instance, Yan et al. (2025) found that AI-driven personalization not only improves skill but also significantly reduces language anxiety by providing a "safe" practice environment. This aligned with the broader meta-analysis by Zai & Zhou (2026), which demonstrated that AI-assisted feedback reshaped learner agency by allowing students to control their pacing and revision cycles in ways traditional classrooms cannot easily replicate.

However, the "High" level of concern regarding overdependence ($M = 3.95$) reflected a critical pedagogical tension. The 2026 studies by Mekheimer (2025) and Braha (2026) warned that while AI boosts immediate output, it can create a "competence-performance gap" if learners bypass the deep processing required for long-term retention. This "cognitive offloading" remained a central theme in the literature, with

Zhai (2024) Zhai et al. (2024) and Al-Qadri & Al-Khresheh (2025) arguing that uncritical reliance on AI dialogue systems could eventually undermine the very critical thinking skills the technology is intended to support. This suggested that the respondents' high scores in this area were not just a fear of technology, but a sophisticated understanding of the "desirable difficulty" needed for true language mastery.

Furthermore, the social and ethical concerns – specifically reduced human interaction ($M = 3.90$) and privacy ($M = 3.87$) – aligned with the 2026 UNESCO Global Education Report and DepEd's 2026 Foundational Guidelines. These reports emphasized that a "human-centered" approach is non-negotiable, a sentiment echoed by Tomczyk and Majkut (2025), who found that trust is often hindered by the "dehumanization" of the feedback loop. The fact that respondents in a regional state college in Bicol shared these global concerns highlighted a universal awareness of the ethical dimensions of AI. Ultimately, the "benefit–risk equilibrium" found in this study affirmed that while the community embraced AI's utility, they demanded a hybrid model – one that retains human mentorship to mitigate the risks of inaccuracies and social isolation.

5.1. Proposed Policy Framework for Improving the Acceptability and Integration of Artificial Intelligence Tools in Autonomous Language Learning

The proposed policy framework was developed as a strategic response to the study's finding that AI acceptability in autonomous language learning is primarily driven by the nexus of perceived usefulness, trust and reliability, and ease of use. By synthesizing these empirical drivers, the framework operationalizes a systems-oriented approach to AI adoption. It addresses both enabling and constraining factors by integrating infrastructure support, pedagogical orchestration, ethical safeguards, and continuous evaluation. Central to this framework is the "Human-in-the-Loop" philosophy, which positions AI as a supplementary, responsibly managed resource rather than a replacement for human instruction. As such, the framework offers a practical, evidence-based model for institutions seeking to foster a high-trust, high-utility environment for language education.

5.1.1. Framework Architecture and Operationalization

The AI Acceptability and Integration Framework (AAIF) utilizes an Input–Process–Output–Outcome (IPOO) model, ensuring that AI adoption is treated as a cyclical, adaptive process rather than a static implementation. This structure aligns with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) by linking institutional inputs directly to user perceptions.

a) Inputs: The framework identifies access, infrastructure, and baseline digital literacy as the foundational requirements. It recognizes that facilitating conditions – such as hardware availability and stable connectivity – provide the necessary "Ease of Use" foundation.

b) Processes: To enhance Perceived Usefulness – the study's strongest predictor of intention ($\beta = 0.46$) – the framework mandates "Pedagogical Orchestration." This involves training faculty to move beyond basic tool usage toward designing AI-integrated curricula that support differentiated and autonomous instruction.

c) Outputs: Through Capacity Building and Quality Assurance, the framework strengthens user confidence. It incorporates "Trust Safeguards," such as regular accuracy audits and "Algorithmic Impact Assessments" (AIA), to address concerns regarding AI hallucinations and stylistic biases.

d) Outcomes: The ultimate goal is the creation of a Sustainable Autonomous Learning Environment. By embedding Ethics and Privacy protocols – aligned with the Philippine Data Privacy Act and the 2026 Responsible AI in Basic Education – the framework ensures that students engage with AI in a cognitively responsible manner, mitigating risks of overdependence and "cognitive offloading."

Ultimately, the framework underscores that successful AI integration in a state college context depends not solely on technological availability, but on a balanced interplay among pedagogical alignment, user trust, and institutional governance. By including a continuous Monitoring and Evaluation (M&E) mechanism, the framework remains responsive to the rapid evolution of generative AI, ensuring that the institution's policy remains as dynamic as the technology itself. This holistic approach fosters an ecosystem where AI augments human potential, leading to more flexible, effective, and ethically grounded language learning outcomes.

6. Conclusion

This study provided comprehensive empirical evidence regarding the multifaceted factors that influenced the adoption of Artificial Intelligence (AI) tools for independent language learning within the state college context. The findings revealed that respondents exhibited high to very high levels of acceptance across all primary dimensions, including perceived usefulness, ease of use, trust and reliability, and behavioral intention. Most notably, the multiple regression analysis identified perceived usefulness as the most potent determinant of behavioral intention, followed by trust and reliability and perceived ease of use. These results indicated that while user-friendliness remained important, learners were primarily motivated to adopt AI technologies when they perceived them as highly effective and academically dependable partners.

The data further demonstrated that learners recognized substantial pedagogical advantages in AI integration, particularly regarding the flexibility of access, the immediacy of feedback, and the capacity for personalized learning pathways. These benefits significantly enhanced the overall language learning experience by fostering a more adaptive and learner-centered environment. Concurrently, respondents maintained a sophisticated "benefit-risk equilibrium" by expressing moderate apprehensions concerning output accuracy, potential overreliance, data privacy, and the possible reduction of human interaction. This critical stance suggested that the participants viewed AI integration through a lens of "cautious optimism," prioritizing functional gains while remaining vigilant of the technology's socio-pedagogical limitations.

A pivotal insight from the inferential analysis revealed that, although prior experience with AI tools was rated highly in descriptive terms, it failed to serve as a significant predictor of behavioral intention within the multivariate model. This finding implied that current cognitive evaluations – specifically the perceived utility and trustworthiness of the system – played a far more decisive role in shaping adoption than mere historical exposure or past usage. Furthermore, the model's robust explanatory power ($R^2 = 0.772$) indicated that the selected variables successfully captured approximately 77.2% of the variance in adoption drivers, confirming the high reliability of the research framework.

Ultimately, these findings reinforced the continued relevance of the Technology Acceptance Model (TAM) in the era of generative AI, while simultaneously highlighting the necessity of trust as a critical extended construct. By demonstrating that behavioral intention was driven by a combination of utility, usability, and reliability, this study provided a clear empirical roadmap for institutional leaders. It underscored that the sustainable integration of AI in language education must move beyond providing technical access and instead focus on enhancing the perceived value and ethical transparency of the tools to ensure they effectively complement the human-led instructional process.

Ethics Approval and Consent to Participate

This study was conducted in strict accordance with the ethical standards of Bicol State College of Applied Sciences and Technology Research Ethics Committee. Formal ethical approval was obtained prior to the commencement of data collection.

All participants – comprising language instructors and students – were provided with a clear and comprehensive Informed Consent Form via the digital survey platform. This document detailed the study's objectives, the voluntary nature of participation, and the right to withdraw at any stage without penalty. Participants provided their explicit consent electronically before accessing the survey instruments.

To ensure the confidentiality and anonymity of all respondents, no personally identifiable information (PII) was collected. All data were encrypted and stored in a secure, password-protected database accessible only to the primary researcher, in compliance with the Philippine Data Privacy Act of 2012 (RA 10173). Upon completion of the statistical analysis, the raw data were handled according to the institution's data retention and disposal policy to prevent unauthorized access.

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Conflict of Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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